

# An image processing Algorithm For Vehicle Detection And Tracking

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# An Image Processing Algorithm For Vehicle Detection And Tracking

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## Certificate

This is to certify that the work in the project entitled *An Image Processing Algorithm For Vehicle Detection And Tracking* by *Soumyashree Seth* is a record of her work carried out under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of *Master of Technology in Computer Science and Engineering*.

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## Abstract

Object detection ,tracking and its velocity estimation play important roles in traffic surveillance system.It's an arising and On-Demand technique in the field of image processing . Real time object track is vital job in many computer vision practical application.Two major components can be distinguished in a typical visual tracker.The picture determination of the feature accessible from most movement camera framework is low. As a rule for following multi item, recognizing them from another isn't simple due to their comparability. In this paper we depict a system, for tracking various items, where the articles are vehicles. The quantity of vehicles is obscure and differs from frame to frame. We identify all moving objects, and for tracking of vehicle we utilize the kalman filter and shading highlight and separation of it from one casing to the following. So the system can recognize and follow all vehicles exclusively. The proposed method can be utilized in numerous moving items. The proposed algorithm uses kalman filter to estimate objects' location,shape and size in a small range and to gain trajectory a of the object. To make visible moving object prominently it is required to remove the noise in the image which is done by morphological operations.Objects are tracked by feature matching in image sequence.Matched objects are numbered same .Then number of objects crossing through a particular line in the image are counted. Finally to figure out rush in traffic area velocity is estimated by averaging the speed of vehicles present in a frame. If average velocity accedes a threshold value,that means heavy traffic is there. Through out the process CCTV camera is considered stationary.

Keywords-Object detection,object tracking,morphological operations, vehicle counting

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# Chapter 1

## Introduction

Constant vehicle following is a basic undertaking in numerous PC vision applications, for example, item based feature pressure surveillance, smart rooms and so on. [?]

One of the noteworthy utilizations of feature based supervision frameworks is the movement reconnaissance. The looks into have examined in the Vision-Based Intelligent Transportation System (ITS), transportation arranging and activity designing applications to concentrate valuable and exact movement data for activity picture examination and movement stream control like vehicle check, vehicle direction, vehicle following, vehicle stream, vehicle arrangement, activity thickness, vehicle speed, movement path changes, tag acknowledgment, and so on. [10]

A top-down procedure information affiliation and Filtering manages elements of the followed objects, learning of earlier scene and assessment of probabilities. The way segments are related and weighted, assumes a definitive part in the productivity and heartiness of the tracker. [3]

The goal of following is to gauge the state  $x_k$  given all the estimations  $z_{1:k}$  up that minute, or proportionately to develop the likelihood thickness capacity  $p(x_k | y_{1:k})$ . The hypothetically ideal arrangement is given by the recursive Bayesian channel which tackles the issue in two stages. To determine probability density function at earlier point  $p(X_k | Z_{1:k-1})$  of the current frame is required to find the pdf of same frame at present time. At that point, the upgrade step utilizes the probability

capacity  $p(X_k | Z_{1:k-1})$  of the current estimation to figure the back pdf.

An Automatic vehicle tallying framework makes utilization of feature information obtained from stationary activity cameras, performing causal scientific operations more than an arrangement of edges got from the feature to gauge the quantity of vehicles present in a casing. It is only the capacity of naturally concentrate and perceive the activity information e.g. aggregate number of vehicles, vehicle number. Counting vehicles and normal speed gives us the data expected to acquire a fundamental seeing over the stream of movement in any district under reconnaissance. Along these lines, the first information we have attempted to accumulate is tallying of vehicles from accessible activity features from different libraries. In every feature outline, Gaussian mixture model separates questions in movement from the foundation by subtracting. The goal of the research is to build up a system that act on footage sequence by stationary CCTV set up near traffic juncture and automatically count the number of vehicles crossing through a spot in a specific time for average velocity estimation and further vehicles information gathering.

Many researchers have been trying to study some automated detection methods. Some similar methods are :

1. Particle filtering method In first stride for particles fitting in with foundation areas that stay static in their spatial positions as per a limit are evacuated. Square coordinating strategy is utilized to discover the movement vector of the key focuses. Particles are assembled utilizing the k-implies calculation. Vehicle identification is in view of the shape and shading of the identified particles. The vehicle following is performed taking into account the likeness of the shading histograms in processed for  $X \times X$  pixel windows focused at the particles fitting in with the curved areas framed by the vehicles in the past casings, moved by their movement vectors to the present edge. This curved area is expanded by couple of pixels to cover new particles. To classify particles Mohalanobis distance is applied. [1]

2. Kernel based object tracking Another methodology toward target representation and restriction, the focal part in visual following of nonrigid items,

is proposed. The highlight histogram-based target representations are regularized by spatial veiling with an isotropic piece. The veiling actuates spatially-smooth likeness capacities suitable for inclination based enhancement, subsequently, the objective restriction issue can be defined utilizing the bowl of fascination of the nearby maxima. We utilize a metric got from the Bhattacharyya coefficient as similitude measure, and utilize the mean movement system to perform the streamlining. In the exhibited following samples, the new technique effectively adapted to camera movement, halfway impediments, disarray, and target scale varieties. Coordination with movement channels and information affiliation strategies is additionally examined. We portray just a couple of the potential applications: abuse of foundation data, Kalman tracking utilizing movement models, and face tracking. [4]

3. Probabilistic Multi-Hypothesis Tracking In a multitarget, multimeasurement environment, learning of the estimation to-track assignments is regularly occupied to the following calculation. This report is a probabilistic way to deal with the estimation to-track task issue; that is, estimation assignments are displayed as discrete arbitrary variables. Estimations are not doled out to particular tracks as in customary multi-Hypothesis tracking (MHT) calculations; rather, the likelihood that each estimation has a place with every track is evaluated utilizing an exact Bayesia calculation. The probabilistic multi-Hypothesis tracking (PMHT) methodology proposed in this report treats target states and estimation assignments as ceaseless and discrete arbitrary variables, individually, furthermore, characterizes a proper joint thickness on these variables. The PMHT estimation calculation is in the class of purported exact Bayesian systems that is, it is a crossover most extreme a posteriori (MAP) and greatest probability (ML) calculation. The PMHT evaluations are

joint assessments of target states and estimation to-track task probabilities.

## 1.1 METHODOLOGY

Methods followed to detect and track moving objects are:

### 1.1.1 Motion Detection and Segmentation Approaches

Image segmentation is performed to identify objects and their boundaries in image. An image is processed and partitioned into multiple segments. Processing an image to partition it into various segments (this might be according to pixel intensities) is called image segmentation.

- Background Subtraction Methods:

The procedure of separating moving foreground items (data picture) from background picture (static picture) or producing background edge structure picture arrangement (feature) is called background subtraction, after that, the removed data (moving articles) is come about as the edge of picture differencing. This technique is one of generally change discovery methods utilized as a part of vehicle areas location. The non-adaptively is a disadvantage which is raised because of the evolving in the lighting and the atmosphere circumstances [10]. Along these lines, a few specialists work to determine this disadvantage by proposed techniques on this field.

A critical commitment proposed the factual and parametric based strategies which are utilized for background subtraction techniques; some of these strategies utilizes the Gaussian likelihood dissemination model for every pixel in a picture. After that, the pixel qualities are upgraded by the

Gaussian likelihood dissemination display these pixel values which are upgraded from new picture in the new picture arrangement. At that point, every pixel(x,y) in the picture is sorted either be a piece of the foreground (moving objects or blobs) or background image as per satisfactory measure of learning aggregated from the model.

- Feature Based Methods
- Frame Deviation and Motion based methods

### 1.1.2 Mathematical Morphology

Binary images are generated by simply thresholding the original image. This might contain errors because choosing appropriate threshold value is very difficult task. Morphological picture handling seeks after the objectives of uprooting these blemishes by representing structure of the picture. These strategies can be reached out to gray scale pictures.

Morphological picture handling is a gathering of operations identified with the shape or morphology of highlights in a picture. Morphological operations rely on upon the relative asking for of pixel qualities, not on their numerical qualities, and consequently are especially suited to the get ready of parallel pictures. Morphological operations can likewise be connected to grayscale pictures such that their light exchange capacities are obscure and along these lines their outright pixel qualities are of no or minor hobby.

Morphological methods test a picture with a little shape or layout called an organizing component. The organizing component is situated at all conceivable areas in the picture and it is contrasted and the comparing neighborhood of pixels. A few operations test whether the component fits inside of the area, while others test whether it hits or crosses the area:

If a structuring element is placed on a binary image each pixel in it is associated with the corresponding neighborhood pixels of the pixels under it. For each pixel in the structuring element set to 1, if the corresponding pixels in the image also set to 1, then the SE is said to fit the image. If for at least one pixel in the Structuring element, the corresponding pixels in the binary image set to 1, then it is called hit.

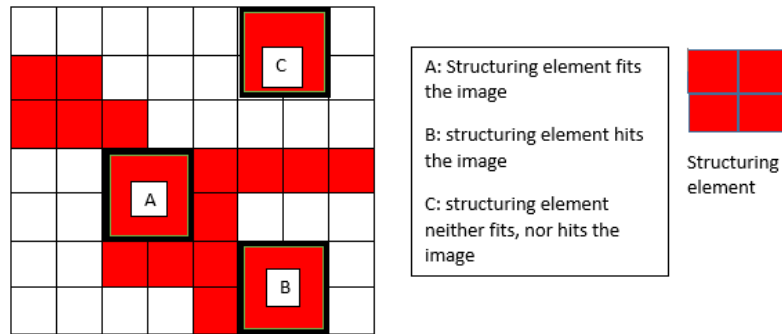


Figure 1.1: Structuring Elements in an image

```

0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 1 1 0 0 0 0 0 0 0
0 0 1 1 1 1 1 0 0 0 0 0
0 1 1 1 1 1 1 1 0 0 0 0
0 1 1 1 1 1 1 1 0 0 0 0
0 0 1 1 1 1 1 1 0 0 0 0
0 0 1 1 1 1 1 1 1 0 0 0
0 0 1 1 1 1 1 1 1 1 0
0 0 0 0 0 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 0 0
    
```

Fundamental operations: Erosion,Dilation

Erosion: Erosion of an image  $I$  by structuring element  $S$  generates new binary image  $g=I \ominus S$  . $g$  will have all ones pixels values .Erosion with very small size structuring element shrinks an image by cleaning its inner pixel layer along with the outer pixel layer.So that gaps between different regions become larger and small areas are cleaned.

Erosion with bigger size structuring element has sound effect .If  $S1$  and  $S2$  are two structuring elements of similar shape with  $S1$  twice the size of  $S2$ , then  $I \ominus S1 = (I \ominus S2) \ominus S2$  Erosion removes all small details ,but reduces the size of regions of interest in the same time.Boundary of each region can be obtained by subtracting



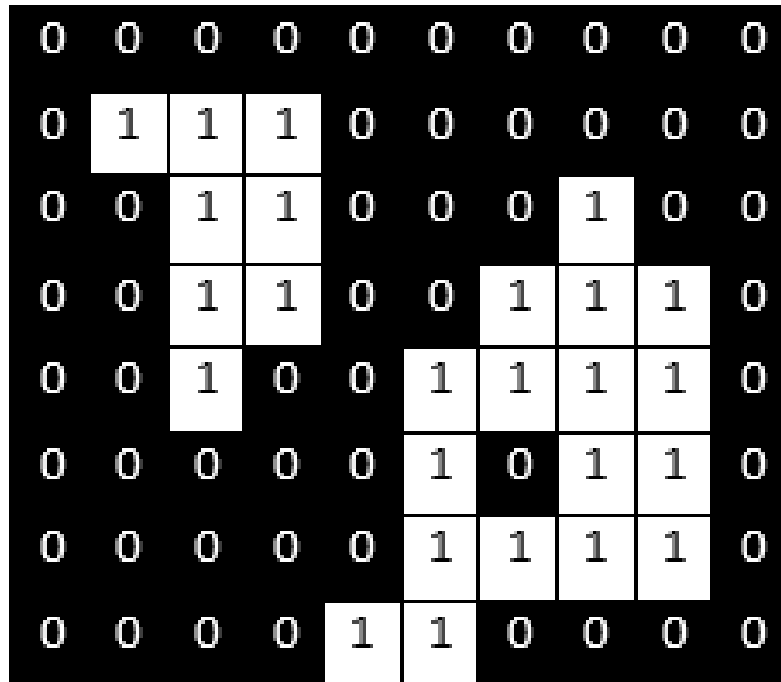


Figure 1.2: Binary Image Before dilation

the eroded area from the original image.  $B=I-(I \ominus S)$ , here B is the boundary of the region.

**Dilation:** Dilation of an binary image by a structuring element is represented by  $I \oplus S$ . It generates binary image with ones in all locations in the original image at which that structuring element hits. Dilation is just opposite to erosion, it adds a layer of pixels to both the inner and outer boundaries of regions. Hence holes between regions become smaller.

Many other morphological operations such as Intersection, Union, opening, closing are combination of both erosion and dilation.

1. Complement :  $I^c(x,y)=1$  if  $I(x,y)=0$  and  $I^c(x,y)=0$  if  $I(x,y)=1$
2. Intersection:  $a=b \cap c$   $a(x,y)=1$  if  $b(x,y)=1$  and  $c(x,y)=1$  otherwise
3. Union :  $a=b \cup c$  where  $a(x,y)=1$  if  $b(x,y)=1$  or  $c(x,y)=1$  and  $a(x,y)=0$  otherwise

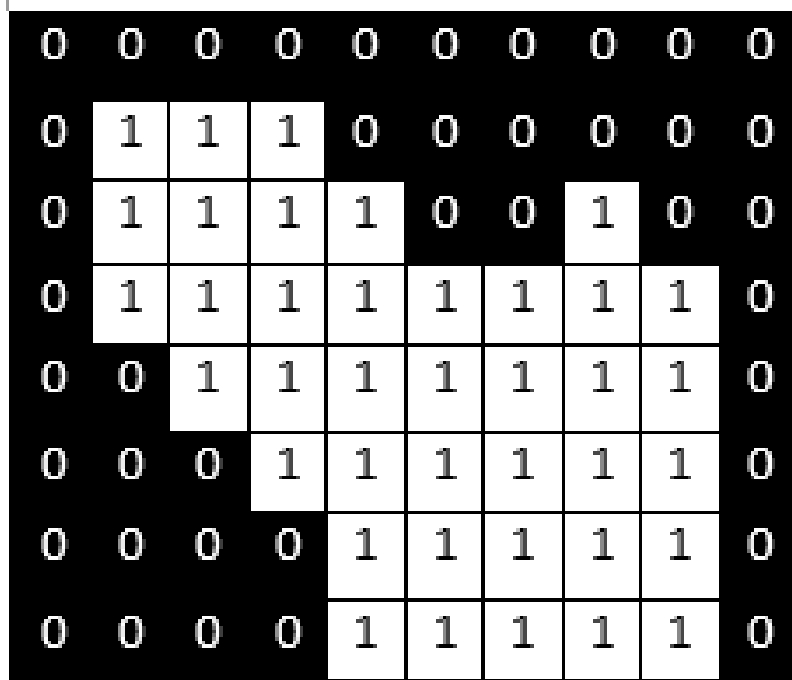


Figure 1.3: Image after Dilation

4. Opening : An erosion followed by dilation morphological operation and is represented as  $a \circ b = (a \ominus b) \oplus b$

5. Idempotent :  $(a \circ b) \circ b = a \circ b$

### 1.1.3 GMM

A heuristic probabilistic model that assumes data points to be generated from finite random numbers that are Gaussian distributed. One can consider blend models as summing up k-means bunching to fuse data about the covariance structure of the information and additionally the focuses of the inert Gaussians.

### 1.1.4 Vehicle Tracking Approaches

#### Region Based Tracking Methods

Shape, position and size of the region in the segmented image is estimated using recursive algorithm. Image is segmented using some motion based segmented algorithm. All the points in a region are then taken in to account to predict the shape and location of the region in the next frame. Motion parameters of the region are estimated and motion model is updated that is compared with the updated geometric model to predict the region in the next frame. Geometric filter and motion filter are used for the estimation.

#### Contour Tracking Method

To figure out the boundary of an object in a digital image contour tracing technique is used. Feature extraction algorithm if applied with this method that reduces the computing time. 4 contour tracking algorithms are Square tracing algorithm

Moore-neighbor tracing

Radial sweep

Theo pavlidis Algorithm

#### 3D Model-Based Tracking Methods

Transformational and rotational motions are the results of decomposition of a 2-D image. These result from movements of 3-D transformation on the ground plane and rotation around the normal of the GP respectively

#### Feature Based Tracking Methods

This method is based on edge points and SHIFT descriptors for matching of features of objects.

**Color and Pattern Based Method**

YCrCb color space is used by author for generation of foreground, background, object location and object tracking.

**1.1.5 Kalman Filter**

Kalman channel is connected to 2 back to back picture outlines for state estimation of a direct system, and the state is thought to be dispersed by a Gaussian. Kalman separating is made out of two stages, expectation and correction. The forecast step utilizes the state model to anticipate the new condition of the estimation parameters. These anticipated parameters help creating new condition of item. Locale based coordinating method kalman sifting is joined with mean-movement to foresee area effectively. To enhance meas-shift concerning scale change, a scale space instrument was presented.

## 1.2 MOTIVATION

Keeping the examination course a stage forward, it has been understood that there are numerous degrees to accomplish the objective. However the proposed method uses background subtraction method ,which detects objects and processed with kalman filtering that reduces the computation time. (1) This method is easier than the robust 3-D Model Based Vehicle Tracking method. (2) In mean-shift blob detection method scale is the crucial parameter, and there is no clean mechanism to choose the scale.

## 1.3 ORGANIZATION OF THESIS

Organization of the rest portion of the thesis is like :

1. Chapter 1: Introduction to methods considered in the project work are discussed and motivation of the project is introduced.
2. Chapter 2: Literature review describing some existing Algorithms to reach the objective is presented in this chapter
3. Chapter 3: All edge detection methods are briefly discussed in this chapter
4. Chapter 4: This chapter contains our proposed method.
5. Chapter 5: Alternate methods towards achieving goal is presented here .
6. Chapter 6: In this chapter the work done is evaluated and at last concluded here.



## Chapter 2

# VEHICLE DETECTION AND TRACKING

### 2.1 LITERATURE REVIEW

In the late years of inquires about, different methodologies have been connected in this specific zone of distinguishing vehicle information yet the crevice is there as it needs change in discovery and following for exact expectation. MVDL-(numerous virtual finder line) based strategy may be exceptionally compelling in astute transportation framework however precision could possibly be palatable in complex activity circumstances [5]

Len at al connected the system of recognizing conceivable vehicles in the predetermined blind side region by coordinating the appearance-based components and edge based elements however the outcomes are marginally unacceptable because of the unpredictable foundation. [6] Food forward neural system has been utilized to recognize the vehicles by P. Rajesh for taking care of issues, for example, grouping, clustering, and capacity close estimation however it needs clear feature data to stop mis-location of vehicles [7].

The methodology has a few constraints as a semantic area could be identified if

walkers as often as possible stroll through a zebra intersection creating trouble on direction bunching. Bouvie et al exhibited an option utilizing molecule movement data yet intruded on activity stream and impediment may minimize the outcomes. Little vehicles can be missed, following the quantity of particles may be inadequate to produce a group. [8]

Soo Siang Teoh and Thomas Braunl proposed a component for vehicle following and controlling in sequential feature casings taking into account Kalman channel and an unwavering quality point framework. The most likely area of an identified vehicle in the ensuing feature casing is anticipated by Kalman channel and this information is utilized by the following capacity to limited down the quest territory for re-recognizing a vehicle. Zhao and Wang have proposed another way to deal with include vehicles complex activity situations by using the data from semantic areas and tallying vehicles on every way independently. [9]

### 2.1.1 Aerial Vehicle Detection

For ethereal vehicle observation numerous vision based calculations have been developed. An calculation that uses picture homography produced from feature arrangement caught by a relentless camera and utilization Probabilistic Multi-Hypothesis following to perceive the drawing closer recognized airborne vehicles. In First step ,questions that are not consistent in respect to two sequential edges are controlled by dark force change for which eigen worth is ascertained by Shi-Tomasi-Kanade tracker. [10]

$$Int = \begin{pmatrix} \Sigma(\frac{\partial I}{\partial x})^2 & \Sigma(\frac{\partial I}{\partial x \partial y}) \\ \Sigma(\frac{\partial I}{\partial x \partial y}) & \Sigma(\frac{\partial I}{\partial y})^2 \end{pmatrix}$$

$$Disp = \begin{bmatrix} d_x \\ d_y \end{bmatrix}$$



$$Int.Disp = Gt$$

$$Gt = \iint_w [I(z, t) - J(z, t)] \begin{bmatrix} g_x \\ g_y \end{bmatrix} W(z) dx dy$$

$$z = \begin{bmatrix} x & y \end{bmatrix}^T$$

Gt is the gray intensity change. I(x), J(x) are images .W is the feature.

Wquation for 2-D homography Estimation

$$z_i \times Hx_i = 0$$

Homography is estimated using direct transformation(DLT) algorithm. Moving object is extracted by subtracting two video image sequence.

Difference between 2 successive image sequence is obtained by

$$\Delta I_{dif} = I_{t-1} - I_t(x, y)$$

Algorithm named Multiple Target Information Management is used for tracking the vehicles.

To classify the vehicle detected as an aerial vehicle, MTIM algorithm with thresholding is followed. Kalman filter is used to determine the same objects in successive frame sequence. This method helps managing hypothesis regeneration by resetting. [11]

### **2.1.2 3-D Model Based Vehicle Tracking**

This is a vigorous system where 2-D picture is break down into 2 movements named interpretation and rotation. A metric in view of point to line section separation is considered to assess the comparability between a picture locale and an instantiation of 3-D model of a vehicle in a specific stance [12].

## **2.2 Summary**

In this chapter, we have described some methods worked on by some researchers.

. []

# Chapter 3

## MIXED EDGE DETECTION MECHANISM

In this part discourse in regards to edge and diverse kind of edge detection of an image are exhibited. Additionally idea of half breed edge are exhibited to endeavor greatest number of edge pixel shown in the spread image.

### 3.1 Edge detection operator

An edge is boundary between image segments.

In image processing, e detection technique is considered as as important mechanism ,most generally in the area of feature sensing and feature extraction,as edge plays an important role in analyzing contained of an image .Edge detection is the process of Identifying the pixels in an image where sharp change in the intensity takes place particularly in the intersection region separate objects [13]. Many edge detection mechanisms that are followed in image processing are:

1. Canny Edge detection
2. Prewitt Edge Detection
3. Sobel Edge Detection

4. Laplacian of Gaussian(Log) Edge Detection
5. Robert Edge Detection
6. Fuzzy Edge Detection

Among the above edge detection methods, the most popular, efficient and widely used edge detection is the canny edge detection mechanism. Good localization, good detection, and single response to an edge are the three important attributes of canny edge operator, for which it is chosen best among the other operator available.

## **3.2 Canny Edge Detector**

The three attributes for which canny edge detector is basically utilized in image processing to locate the sharp brightness change and the item limits in a picture are:

- All the vital edges are safeguarded, no false edges are considered and in the meantime extent of blunder discovery ought to be low.
- Least separation ought to be kept up between the genuine and found position of the edge.
- It response once to a single edge.

Canny edge detector considers a pixel as an of edge,if its gradient magnitude of that pixel is more than the gradient magnitude of pixels present in its either sides and towards most intensity modification. Implementation of Canny edge detection mechanism is like:

- 1 At first, input image is polished by employing Gaussian filter .Standard deviation is kept fixed ,that reduces noise. ( $\rho$ ) .

- 2 At each point edge direction  $\tan^{-1}\left(\frac{g_x}{g_y}\right)$  and gradient magnitude  $g_x^2 + g_y^2$  are calculated. A pixel is considered as an edge point whose value is locally maximum towards the gradient.
- 3 Edge focuses chose in past step offer rising to edges in the slant size of picture. The estimation then tracks along the most astounding purpose of the edges and sets to zero, all the pixels that are not so much on the edge beat to give a slim line in the yield. This system is known as non-maximal covering. The edge pixels are then limit by supposed hysteresis thresholding, which is in view of utilizing two limit  $Th_1$  and  $Th_2$ , with  $Th_1 < Th_2$ . Strong edge pixels are those which has pixels values larger than  $Th_2$ . And weak edge pixels are those whose pixels values lies between  $Th_1$  and  $Th_2$ .
- 4 Finally, Edge linking is performed by integrating weak pixels which are 8-connected to the strong pixels and weak edges are removed by hysteresis threshold.

### 3.3 Laplcian of Gaussian(Log)edge detection

Noise is the main cause for the performance reduction, so before enhancement of edge, edge smoothing is done. The picture is polished by convolution between Log administrator and Gaussian formed bit took after by the utilization of Laplacian administrator.

Gaussian equation is like:

$$Ga(x, y) = e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3.1)$$

An image is blurred if smoothing function  $\sigma$ -standard deviation, is convolved with the image.  $\sigma$  is the one which degree of blurring is determined by

Laplacian of Gaussian is like :

$$\nabla^2 Ga(x, y) = \frac{\partial^2 Ga(x, y)}{\partial x^2} + \frac{\partial^2 Ga(x, y)}{\partial y^2} = \left[ \frac{x^2 + y^2 - 2\sigma^2}{\sigma^4} \right] e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3.2)$$

The laplacian  $La(x, y)$  of an image with pixel intensity  $I(x, y)$  is given by :

$$La(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \quad (3.3)$$

Convolution of image with  $\nabla^2 G(x, y)$  has two effects. (a) It polishes the image by reducing noise.

(b) Laplacian is computed to yield a double edge image.

### 3.4 Mixed or Hybrid edge detector

The hybridization happens by the Log edge indicator and canny edge locator. This hybridization helps in discovering more measure of edge pixel in the picture alongside clear, exact item limits in the picture. Half and half edge locator discover the item limits that are obviously better than those are created by both of vigilant edge or log edge identifier.

### **3.5 Summary**

In this section, a profundity discourse in regards to two most essential edge recognition component are exhibited. Alongside advantages and disadvantages of watchful edge and log edge identification system, it likewise depict how to adventure most extreme number of edge from picture. The test result likewise showed with suitable test pictures.

# Chapter 4

## VEHICLE DETECTION AND TRACKING

There are many features of a vehicle (color,size,edge) that can be considered for its tracking. The new object comes into a video just then can be identified easily by subtracting the previous frame from the current frame. That will take off the common features in previous and current frame leaving the appeared new feature like that in current frame.

### 4.1 OBJECT DETECTION METHOD

#### 4.1.1 Background Subtraction

Both feature based and Region based tracking algorithms are used to track the object. Gaussian Mixture Model is used for background subtraction. Here camera position is considered stationary and brightness effect is neglected. Video frame at time  $t$  is subtracted from the video frame at time  $t+1$ . Consider  $B_0(i,j)$  is the background image initialized as  $B_0(i,j)=I_0(i,j)$   $I_0$  is the first frame in the video. We



will get the mask by thresholding the subtracted image. Equation is like

$$M(i, j) = \begin{cases} 1 & \text{if } I(i, j) - B(i, j) \geq \text{threshold} \\ 0 & \text{otherwise} \end{cases} \quad (4.1)$$

Extended background subtraction equation

$$M(i, j) = \begin{cases} 1 & \text{if } I(i, j) - (\alpha * I(i, j) + (1-\alpha) * B(i, j)) \geq \text{threshold} \\ 0 & \text{otherwise} \end{cases} \quad (4.2)$$

Another equation for foreground subtraction of the image, and that was used in our project is

$$M(i, j) = \begin{cases} 1 & \text{if } I(i, j) - B(i, j) + \text{sign}(I(i, j) - B(i, j)) \geq \text{th} \\ 0 & \text{otherwise} \end{cases} \quad (4.3)$$

$$\text{th} = \text{temp1} + \text{sign}(N * \text{sign}(I(i, j) - I_t(i, j)) - \text{temp1}) \quad (4.4)$$

$B$  is the initial grayscale image.  $\text{temp1}$  contains value 1, 0 or -1 the sign of pixels in the initial frame.  $\text{th}$  is the threshold.

Adaptive background subtraction method uses  $\alpha = 1$  or  $0$  time constant, a parameter that controls the rate of adaptation of background. The binary mask contains values only 1 or 0. Regions that contain value 1 signify some objects that are imparted into the initial image.  $M$  is binary mask of the frame sequence. [14]

Figure(a) is a random image from a image sequence and Figure(b) is the corresponding binary image generated after applying extended Background Subtraction Method. Binary 1 area in Figure(b) are the blobs present in Figure(a).



Figure 4.1: Image Before background Subtraction

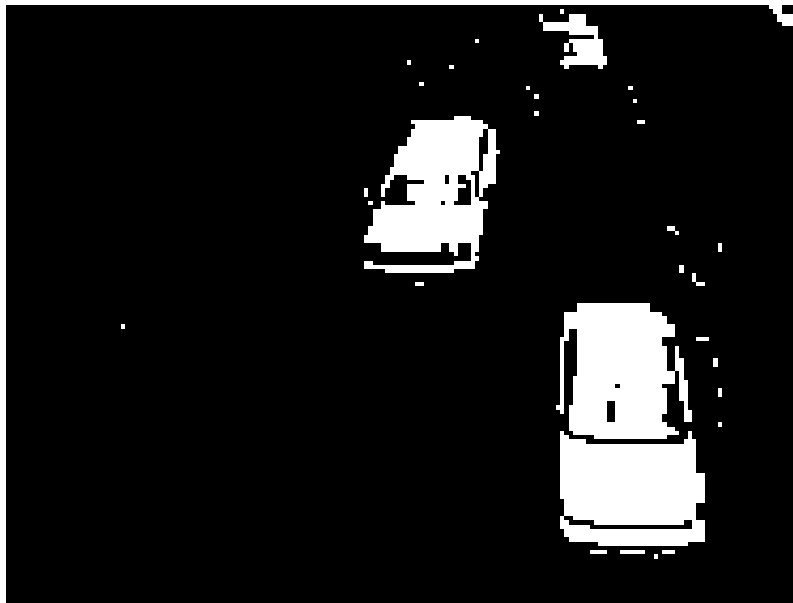


Figure 4.2: Image After Background Subtraction

## ALGORITHM FOR BACKGROUND SUBTRACTION

BG-SUBTRACTION(Image)

---

**Algorithm 1** REMOVE-PARTICLE(MASK)

---

```

1:  $[row\ col] \leftarrow SIZE(image)$ 
2: For  $i \leftarrow 1$  to row
3: For  $j \leftarrow 1$  to col
4:  $Temp1 \leftarrow sign(B(i,j) - Temp(i,j))$ 
5: End
6: End
7: For  $k \leftarrow 1$  to  $nf-1$ 
8:  $I \leftarrow frame\ k$ 
9:  $threshold \leftarrow Temp1(i,j) + sign(N * sign(I(i,j) - Temp(i,j)))$ 
10: For  $i \leftarrow 1$  to row
11: For  $j \leftarrow 1$  to row
12: if  $abs(I(i,j) - (Temp(i,j) + sign(I(i,j) - Temp(i,j)))) \geq threshold$   $Mask(i,j) \leftarrow 1$  else
     $Mask(i,j) \leftarrow \{0\}$  End End

```

---

**4.1.2 Removing Errors**

After background subtraction, we are left with binary mask of the successive image sequence of the video. The mask may contain some erroneous data, that may be the cause of either brightness effect of the camera or the pollution in the air. As camera is considered as stationary, that is not the cause of the problem. Those errors are removed by brute force method. Again dilation is applied to prominent the shape and size of the objects in the objects. Pixel value is substituted by the maximum pixel value from the 8 neighbor pixel values.

To make the objects prominent and to reduce blank space formed in the binary image due to convergence of camera brightness and blob color dilation, a

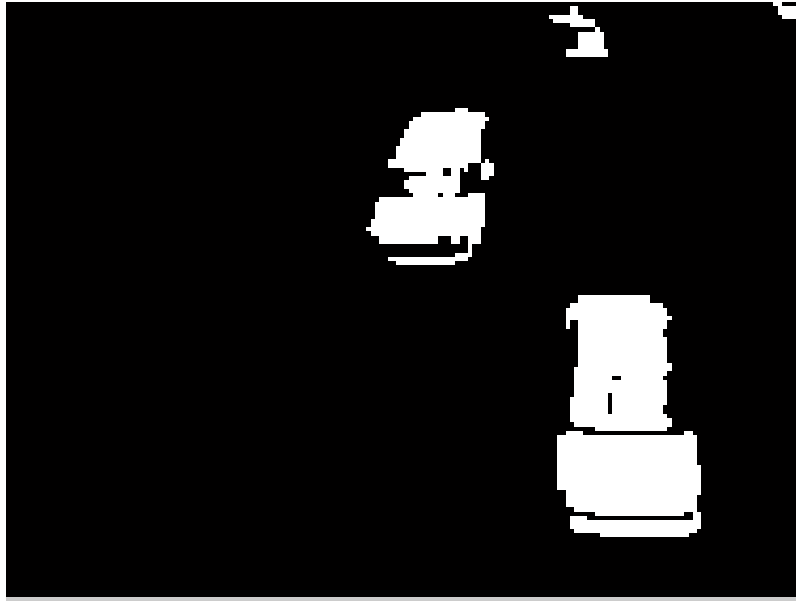


Figure 4.3: Image after removing errors

mathematical morphology method is applied. It gives the actual shape and size of the object in the frame. A random image generated after dilation is shown below.

#### ALGORITHM FOR REMOVING PARTICLE DETAILS

---

##### **Algorithm 2** REMOVE-PARTICLE(MASK)

---

```

1: For  $i \leftarrow 2$  to  $row-1$ 
2: For  $j \leftarrow 2$  to  $col-1$ 
3:  $Count \leftarrow$  total adjacent pixels having value 1
4: If(  $count \leq 4$ )
5:  $Mask(i,j) \leftarrow 0$ 
6: End
7: End
8: End
9: End
10:

```

---

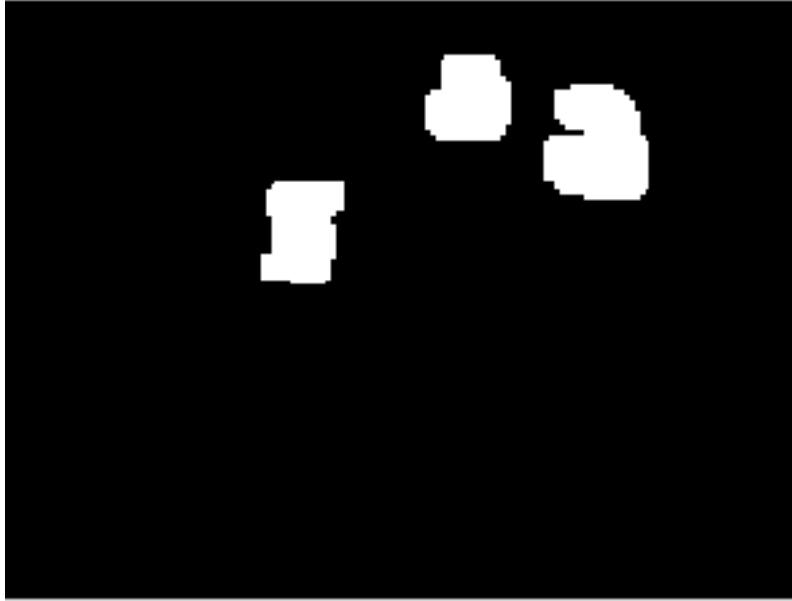


Figure 4.4: Image after dilation

## 4.2 OBJECT TRACKING METHOD AND COUNTING

### 4.2.1 Kalman Filter

To track the objects or blobs, it is required to compare the blobs in consecutive frames. Prediction of the shape and size of the object in the next frame and correction is accomplished by Kalman filtering the image. [14] In Object tracking system Kalman filter  $X_k$  state vector represents the dynamic behaviour of the object, here  $k$  represents the discrete time. The equation is like

$$X_k = AX_{k-1} + W_{k-1}$$

Where  $A$  is the transition matrix.

$$A = \begin{pmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad (4.5)$$

$W$  is the Gaussian process noise

$$R = \begin{bmatrix} 0.2845 & 0.0045 \\ 0.0045 & 0.0455 \end{bmatrix} \quad (4.6)$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad (4.7)$$

Time update equations of the probability distribution  $P$  and the state  $X_k^2$  are

$$\hat{X}_k^- = A\hat{X}_{k-1} + W_k \quad (4.8)$$

$$P_k^- = AP_{k-1}A^T + Q \quad (4.9)$$

Equations to update measurements like covariance error

$$K = P^- H^T (H P_k^- H^T + R)^{-1} \quad (4.10)$$

$$actual = predicted + K(Z_k - H * predicted) \quad (4.11)$$

$$Pr = (1 - KH)P^- \quad (4.12)$$

$k$  is kalman gain. To get the actual one the predicted measurements are computed with recursively generated time and measurement equations.

### 4.2.2 Multiple Object Track

To keep track of objects in one frame to the next frame shape and size of the objects are compared to get the appropriate match. Geometric features of the objects are shape, size, centroid etc. Tracking window size is taken slightly larger than the object

size to avoid noise interference,also make the computation process efficient. Model for motion estimation is

$$X_t = [x_{0,t}, y_{0,t}, v_{x,t}, v_{y,t}] \quad (4.13)$$

$x_{0,t}$  and  $y_{0,t}$  are horizontal and vertical centroid coordinate respectively.

### 4.2.3 Matching Features

A feature in one frame is very similar to the feature in next frame which differ very less in their size and nearest feature with respect to their position.

Distance between objects is measured by equation

$$Distance(i, j) = \sqrt{(x_t^i - y_{t+1}^j)^2 + (y_t^j - y_{t+1}^i)^2} \quad (4.14)$$

Difference in area between the features is computed by equation

$$Area(i, j) = |A_t^i - A_{t+1}^j| \quad (4.15)$$

$A_t^i$  and  $A_{t+1}^j$  represents the  $i$ th object's area in previous frame and  $j$ th object's area in current frame respectively.

Some computation parameter  $\alpha$  is used in the cost function .

$$C(i, j) = \alpha Distance(i, j) + (1 - \alpha)A(i, j) \quad (4.16)$$

$\alpha=0.8$  here. Object with minimum cost is considered as the similar one.

Some cases that appears during match of the features

- CASE 1: Object from current frame is matched with objects in previous frame one by one.As vehicles are moving in forward direction there will be some non-zero velocity and difference in Y-coordinates of centroids of two matched objects in previous frame to current frame should be negative. So during counting if the difference comes wrong that means if it is positive ,that means

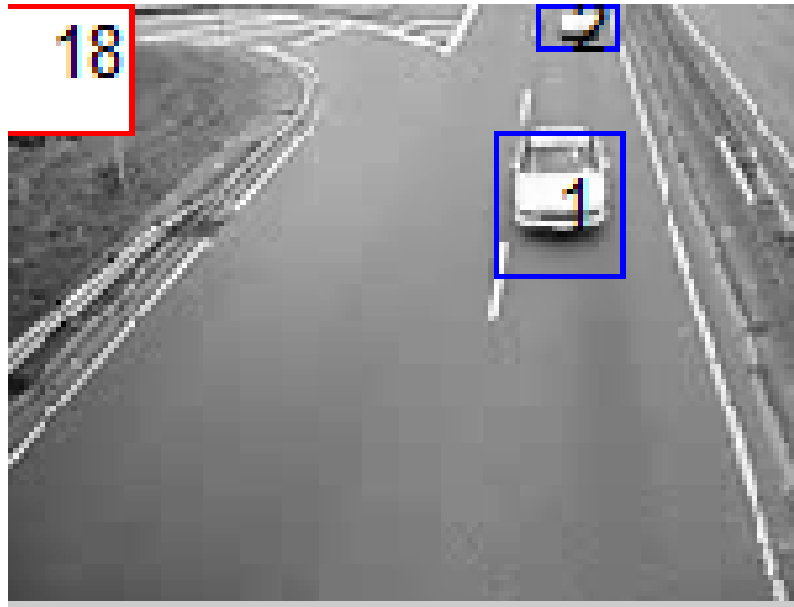


Figure 4.5: frame 18

object in previous frame estimated to be the same with the object in current frame are not same .Hence counter will be incremented by one and that object will be numbered by that counter.

- CASE 2: If matching found between object in current frame that crosses upper the boundary with object in previous frame that does not cross the frame upper boundary,then also that object will be numbered with a new number.
- CASE 3: If object in current frame not having pixels index of lower boundary is matched with an object of previous boundary having pixels index,that means both objects are not same objects.

Following are some random images in the video after feature matching.

#### 4.2.4 Velocity Estimation

Velocity in a frame is calculated by averaging the speed of the vehicles in the frame.

Formula for speed



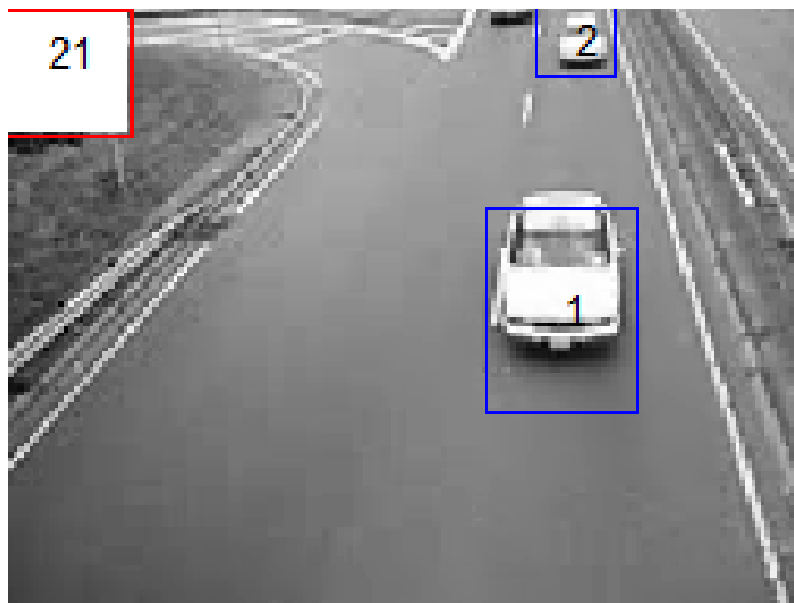


Figure 4.6: frame 21

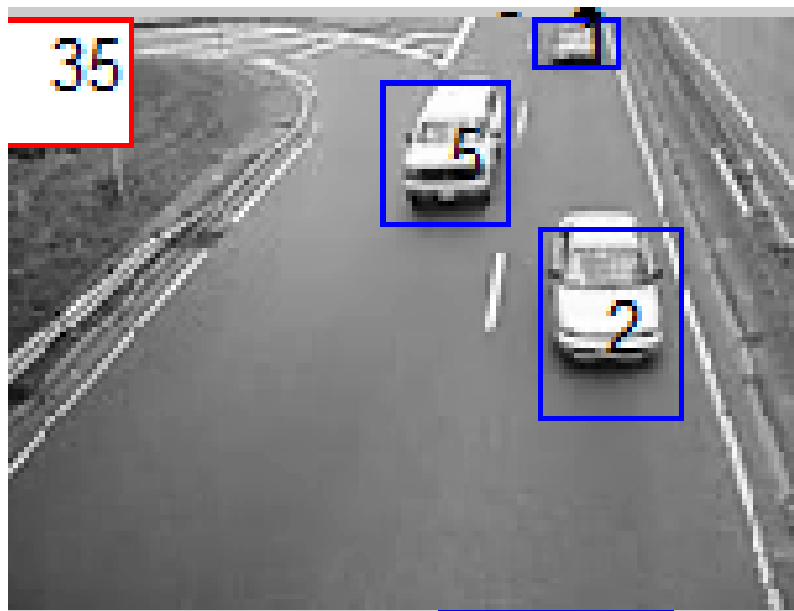


Figure 4.7: frame 35

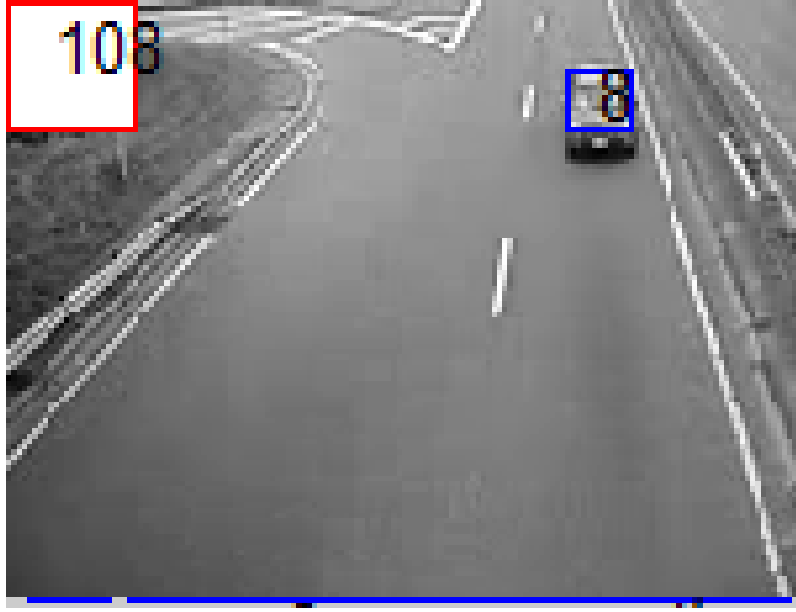


Figure 4.8: frame 108

$$speed(i) = \frac{centroid_{co_i} - centroid_{po_j}}{\Delta t} \quad (4.17)$$

speed(i) is the speed of ith object in current frame.  $centroid_{co_i}$  and  $centroid_{po_j}$  are the same object centroids in current frame and the frame at earlier point.  $\Delta t$  is the time difference. Here  $t=1$ ;

Average velocity in a frame is calculated by formula

$$AV_{f_a} = \frac{\sum_1^n speed(i)}{n} \quad (4.18)$$

$AV_{f_a}$  represents the average velocity in frame a and the number of vehicles in that frame is n.

#### 4.2.5 Traffic Surveillance

Average velocity is thresholded to determine the traffic weight. If  $AV_{f_a}$  exceeds the threshold that signifies heavy traffic. Traffic will be controlled keeping all these in to point.

### **4.2.6 Updating Model**

Once the minimum cost objects are found ,next frame features to update the kalman filter models' parameters.And is used as input in the next frame.This procedure is repeated until the object disappears.

# Chapter 5

## VEHICLE DETECTION AND TRACKING USING EDGE DETECTION METHOD

### 5.1 OBJECT DETECTION METHOD

Other than using GMM(Gaussian Mixture Model) for background the subtraction and blob detection we can first detect the key points or to extract the shape ,areas of the objects in the image edge detection method method can be opted . This edge detection method is followed by background subtraction method to get the moving objects removing stationary pixels or pixels belonging to original image edge.

Steps of Canny Edge Detection

- step 1. Apply canny edge detection method to initial frame and subsequent frames to detect the edge. Canny edge detection method is chosen as Cannys edge detection algorithm has a better performance. [13]
  - (a) Canny operator uses Gaussian filter exclusively to compute image mask. Once the suitable mask ia computed, Gaussian smoothing using convolution is performed. The mask used for convolution is generally much much smaller

than the size of actual image. Thus, the veil is slid over the picture, controlling a square of pixels at once. The detector's sensitivity strength to noise varies as per the size of Gaussian mask. Bigger the width of the Gaussian veil, the lower is the finder's sensitivity to clamor. As per increment in Gaussian width, there is slight increase in localization error of detected edges.

Equation for a Gaussian filter kernel with the size of  $2k+1 \times 2k+1$  is

$$H_{ij} = \frac{1}{2\pi\sigma^2} * \exp\left(-\frac{(i-k-1)^2 + (j-k-1)^2}{2\sigma^2}\right) \quad (5.1)$$

5x5 Gaussian filter, used to create the image to the right, with  $\sigma = 1.3$  (The asterisk denotes a convolution operation.)

$$\mathbf{B} = \frac{1}{159} \begin{pmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{pmatrix} * \mathbf{A} \quad (5.2)$$

(b) First derivative of the values are executed by edge detection mechanisms to find edge gradient in x (horizontally ( $G_x$ )) and y (vertically ( $G_y$ )) direction.

$$\mathbf{G} = \sqrt{\mathbf{G}_x^2 + \mathbf{G}_y^2} \quad (5.3)$$

$$\Theta = \text{atan2}(\mathbf{G}_y, \mathbf{G}_x) \quad (5.4)$$

(c) Once gradient in x and y directions are derived, edge direction can be found easily. If x-direction gradient comes zero, both 90 degree and 0 degree edge directions have to be accounted for the edge direction. Finally the edge direction has to depend on the gradient in y direction. If it comes 0, then direction of edge will be along 0 degree and if gradient in y direction comes 90 degree, then edge will be along 90 degree. Formula for getting edge direction:



Figure 5.1: Image after applying canny filter

$$theta = invtan(Gy/Gx) \tag{5.5}$$

(d)Once direction of edge is known,the direction of edge is related to the direction which can be tracked from an image.Consider a 5x5 pixels image

$$\begin{matrix}
 1 & 1 & 1 & 1 & 1 \\
 1 & 1 & 1 & 1 & 1 \\
 1 & 1 & 0 & 1 & 1 \\
 1 & 1 & 1 & 1 & 1 \\
 1 & 1 & 1 & 1 & 1
 \end{matrix} \tag{5.6}$$

one can notice four directions of the pixel 0, 0 degrees (horizontally), 45 degrees (in direction of positive diagonal), 90 degrees (vertically), or 135 degrees (in direction of negative diagonal).Hence edge orientation will be along the direction which is closest one.(If it comes 10 degree round it to 0 degree).

- step 2. Subtract the produced initial frame from the produced subsequent



Figure 5.2: Image after background subtraction

frames, that detects the moving objects.

- step 3. Filter the image by pixel manipulation and apply dilation to make them prominent.
- step 4. Compare objects between current and previous frame for object matching.

#### ALGORITHM FOR DETECTING AND TRACKING VEHICLE

1. for  $f \leftarrow 1:nf$
2.  $B \leftarrow \text{cannyf}(\text{IMAGE}(f))$
3. for  $i \leftarrow \text{row}$
4. for  $j \leftarrow \text{col}$
5.  $BW(i,j) \leftarrow BW(i,j) - \text{Backgroundedge}(i,j);$
6. END
7. END
8.  $BW2 \leftarrow \text{removenoise}(BW)$
9.  $BW2 \leftarrow \text{dilate}(BW)$

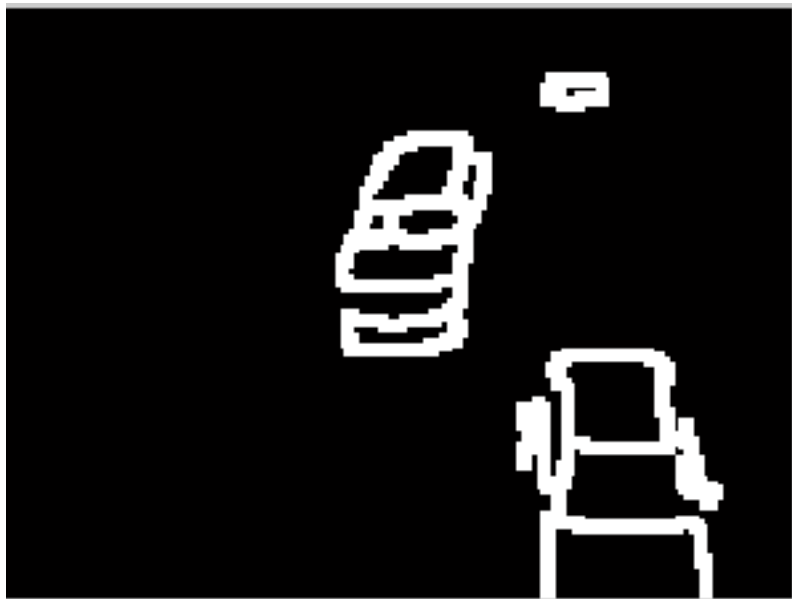


Figure 5.3: Image after pixel manipulation and dilation

10.Feature Matching(CBW2,PBW2)

11.END



# Chapter 6

## EVALUATION AND CONCLUSION

### 6.0.1 EVALUATION

If average velocity per number of vehicles in a frame is thresholded. If it comes less than the threshold value, that means there is heavy traffic.

Total number of vehicles in the traffic video is 10 and number of vehicles detected and tracked automatically using the algorithm is 11.

Table 6.1: The performance comparison of Vehicle Detection Algorithm with Similar Method.

Proposed Method			Existing Method		
Exact quantity Of Vehicles in original Video	Vehicles Calculated	Accuracy	Exact quantity Of Vehicles in original Video	Vehicles Calculated	Accuracy
10	11	90.90%	10	13	76.92%

## **6.0.2 CONCLUSION**

A straightforward and successful framework which tackles the issue under study has been created. The identification of vehicles in a blend activity circumstance of low, medium and high movement is unequivocally of course and the tallying calculation is precise. The constraint of the created technique is that for each camera information bolster a lot of tuning of the parameters is obliged to accomplish the best execution. Additionally, it requires fairly all the more preparing time in profoundly dense activity conditions.

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